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THE EFFECT OF THE WALKING SPEED ON THE STABILITY OF THE ANTERIOR CRUCIATE LIGAMENT DEFICIENT KNEE

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ABSTRACT

Background: The reasons behind the development of future pathology in individuals with anterior cruciate ligament deficiency are unknown. This is due to the lack of appropriate methods to assess functional dynamic knee stability. In this study, we investigated the effect of walking speed on the functional dynamic stability of the anterior cruciate ligament deficient knee. We defined functional dynamic stability as local stability or the sensitivity of the knee to small perturbations. The natural stride-to-stride variations that exist during locomotion reflect exactly the presence of these perturbations. We hypothesized that speed will affect local stability in the deficient knee, especially when compared with the contralateral intact.

Methods: Ten subjects with unilateral deficiency walked on a treadmill at their self-selected speed, 20% faster, and 20% slower, while kinematic data were collected (50Hz) for 100 consecutive footfalls for each condition. The largest Lyapunov Exponent of the resulted knee joint flexion-extension time series was calculated to quantify local stability.

Findings: The deficient knee was significantly more locally unstable than the contralateral knee. Furthermore, increases in walking speed increased did not affect local stability for our subject population.

Interpretations: The altered local stability may render the deficient knee less adaptable to the ever-changing environmental demands. This may explain the increased future pathology found in these knees. However, future efforts should attempt to evaluate this speculation using longitudinal studies. We also propose that the tools utilized in this study can be used eventually to assess functional dynamic knee stability in clinical gait analysis.

Keywords: Locomotion; variability; knee functional dynamic stability; anterior cruciate ligament deficiency.

INTRODUCTION

The anterior cruciate ligament (ACL) is an important stabilizer of the knee joint. This is due not only to the mechanical properties of the ligament but also to the afferent information provided to the central nervous system by the mechanoreceptors that exist in the ACL (Sjolander et al., 2002; Johansson et al., 1991; Solomonow and Krogsgaard, 2001). The loss of the ACL is associated with excessive anterior tibial translation (McDaniel & Dameron, 1980; Marans et al., 1989). Furthermore, ACL deficiency has been related to alterations in joint movement patterns during locomotion (Berchuck et al., 1990; Georgoulis et al., 2003; DeVita et al., 1997) and increased amount of osteoarthritis and meniscal injuries in the knee joint (Hawkins et al., 1986; McDaniel & Dameron, 1980; Daniel et al., 1994). However, the underlying mechanisms responsible for this behavior of the ACL deficient knee have not been understood. Assessing the functional dynamic knee stability (i.e., the stability of the knee during gait) can enhance our understanding of these mechanisms.

The evaluation of functional dynamic stability has been conventionally related to stride-to-stride variability (i.e. the variations that occur across subsequent strides), in terms that increased variability signals increased instability (Holt et al., 1995; Winter, 1989; Yack and Berger, 1993; Maki, 1997). Using traditional methods (i.e. standard deviation, coefficient of variation) stride-to-stride variability has been examined in relation to walking speed and it has been demonstrated that variability increases when healthy individuals walk faster or slower than their free selected pace (Winter, 1983; Rosenrot et al., 1980; Oberg et al., 1993). Researchers have also studied walking patterns in the elderly and the neurological impaired (Dingwell and Cavanagh, 2001; Hausdorff et al., 2000; Hausdorff et al., 2001; Kurz and Stergiou, 2003; Maki, 1997) and found that such subjects exhibit slower walking speeds and increased stride-to-stride variability when compared to controls which indicates decreased functional dynamic stability. Regarding neuropathic patients, it has been suggested that they slow down to ameliorate dynamic stability (Courtemanche et al., 1996), because they are at a greater risk of falling. On the other hand, it has been demonstrated (Dingwell and Cavanagh, 2001; Kurz and Stergiou, 2003) that even though these patients walk slower they exhibit increased variability, which contradicts the previous assumption. This paradox could be due to the fact that the conventional tools are not sufficient enough for the evaluation of functional dynamic stability. Indeed, Dingwell et al. (Dingwell et al., 2000) using nonlinear measures showed that neuropathic patients walk slower but have increased stability when compared to controls. The insufficiency of the linear tools is probably due to the fact that they conceal the temporal variations of subsequent strides. Furthermore, the statistical processing of linear measures requires random and independent variations between subsequent strides. However, recent studies (Dingwell and Cusumano, 2000; Hausdorff et al., 1995) have shown that such variations are distinguishable from noise and may have deterministic origin indicating that subsequent strides are neither random nor independent.

Nonlinear measures, such as the Lyapunov Exponent (LyE) can overcome these problems since they can measure the behavior of a continuously changing system over time such as the human locomotor system during gait (Dingwell and Cusumano, 2000; Stergiou et al., 2004). Furthermore, nonlinear measures have been utilized to examine gait patterns and functional dynamic stability in patients with neurological diseases and in the elderly (Dingwell and Cusumano 2000; Dingwell et al., 2000; Buzzi et al., 2003).

The purpose of this study was to investigate the effect of walking speed on functional dynamic stability of the ACL deficient knee using nonlinear measures. We investigated functional dynamic stability in terms of “local” stability (Dingwell and Cusumano, 2000). Dingwell and Cusumano (Dingwell and Cusumano, 2000) defined local stability as the sensitivity of the system to small perturbations. The natural stride-to-stride variations that exist during locomotion reflect exactly the presence of these perturbations. Local stability can be measured directly using LyE. In the present study we explored the effect of walking speed on the local stability of the ACL deficient knee. Specifically, we hypothesized that changes in walking speed will significantly reduce local stability (i.e. promote instability) in ACL deficient individuals. This effect will be greater for the ACL deficient knee when compared with the contralateral intact knee.

METHODS

Experimental Procedures

Ten subjects (8 males, 2 females; mean age 35.1 [SD 11.2 years], mean mass 78.5 [SD 16 kg], mean height 171 [SD 9.9 cm]), that were diagnosed with an ACL rupture using MRI scans, volunteered for the study. In seven cases the diagnosis was later confirmed with knee arthroscopy. The mean time range from injury to test was 33.5 months. Clinically, the level of deficiency was evaluated with physical examination using the Lysholm score (mean 66 [SD 15]) and static measurement of tibial translation using the KT-1000 (Medmetric Corporation, San Diego, CA, USA; side-to-side differences more than 3.5 mm). All subjects signed an informed consent. In addition, their physicians provided permission for their participation.

The subjects walked on a motorized treadmill (SportsArt 6005; SportsArt America, Woodinville, WA, USA). A 6-cameras optoelectronic system (Peak Performance Technologies, Inc., Englewood, CO, USA) was used to capture the movements of fifteen reflective markers placed on selected bony landmarks of the lower extremities and the pelvis using the model described by Davis et al., (Davis et al., 1991). The reflective markers were placed on the skin surface of both anterior superior iliac spines, mid thighs, lateral femoral epicondyles, mid tibias, lateral malleoli, outsole of the shoes approximately at the second metatarsal heads, heels and the sacrum (Davis et al., 1991). The markers were positioned on all subjects by the same examiner. Using anthropometric measurements and the position of the reflective markers, we calculated three-dimensional knee joint angular displacement, using the algorithms described by Davis et al. (Davis et al., 1991). In the present study we only examined the sagittal knee angular displacement (flexion/extension) of the knee. However, we collected three-dimensional data instead of two-dimensional to minimize potential out-of-plane measurement error (Areblad et al., 1990). In addition, we chose to examine only the sagittal knee angular displacement, because kinematic data from the other two planes, collected via skin markers, have been associated with increased amount of error (Reinschmidt et al., 1997a; Reinschmidt et al., 1997b; Cappozzo et al., 1996). Specifically, Reinschmidt et al. (1997a) compared skin markers and bone pins during running and found good agreement only for knee flexion/extension. For the other two planes of motion, they identified that the average errors relative to the knee range of motion were 63% for internal/external rotation, and 70% for abduction/adduction. Even though walking has less skin movement than running, the errors could still be substantial. Increased amount of measurement error in the data can mask the true nature of variability and can possibly lead to incorrect conclusions, especially, when nonlinear methods are being used (Rapp, 1994).

All subjects were given ample time to warm up and familiarize with walking on the motorized treadmill at their self-selected pace. This pace represented their most comfortable and natural walking speed. Based on this pace, two new speeds were determined for each subject: one faster (20% larger) and one slower (20% smaller). The selection of this percentage was based on the following. The literature has shown that the average preferred walking speed for young healthy adults is 1.4ms^{-1} (Laurent and Pailhous, 1986; Murray et al., 1966). The transition from walking to running usually occurs at 2ms^{-1} (Nilsson and Thorstensson, 1989). Therefore, by increasing the walking speed by 20%, we avoided such a transition. Furthermore, such increments of speeds (20% of the self selected pace) have been used to examine the effect of walking speeds on biomechanical parameters because they are large enough to elicit differences between conditions (Voloshin, 2000). For every speed, once subjects were comfortable walking on the treadmill, data were collected continuously for two minutes at 50 Hz. The collected data represented at least 100 continuous walking strides. Lastly, the mean comfortable self-selected speed used by the subjects in the present study was 0.78 (SD 0.18) ms^{-1}.

Data Analysis

The unfiltered knee angular displacement (flexion/extension) time series were analyzed using nonlinear measures (Kaplan and Glass, 1995). Each time series consisted of 5750 data points, which is considered sufficient for this type of analysis (Stergiou et al., 2004). For a more accurate representation of the variability within the system, the data were analyzed unfiltered (Mees and Judd, 1993). Furthermore, it was assumed that since the same instrumentation was used for all subjects, the level of measurement noise would be consistent for all subjects and that any differences could be attributed to changes within the system itself (Wolf et al., 1985). Therefore, filtering the data may have eliminated important information and provided a skewed view of the system's inherent variability (Rapp, 1994).

Local stability was quantified using nonlinear time series parameters (Dingwell and Cusumano 2000; Dingwell et al., 2000; Dingwell et al., 2001; Buzzi et al., 2003). These parameters are based on examining the structural characteristics of a time series that is embedded in an appropriately constructed state space. An appropriate state space is a vector space where the dynamical system can be defined at any point (Abarbanel, 1996). To properly reconstruct a state space, it is essential to quantify an appropriate time delay and embedding dimension for the investigated time series. Investigation of the characteristics of the state space is a powerful tool for examining a dynamic system because it provides information that is not apparent by just observing the time series (Abarbanel, 1996; Baker and Gollub, 1996). To reconstruct the state space, a state vector was created from the time series. This vector was composed of mutually exclusive information about the dynamics of the system (Equation 1).

$$\mathbf{y}(t) = [x(t), x(t-T_1), x(t-T_2), \ldots] \qquad \text{Equation (1).}$$

where $\mathbf{y}(t)$ was the reconstructed state vector, $x(t)$ was the original data and $x(t-T_i)$ was time delay copies of $x(t)$. The time delay (T_i) for creating the state vector was determined by estimating when information about the state of the dynamic system at $x(t)$ was different from the information contained in its time-delayed copy. If the time delay was too small then no additional information about the dynamics of the system would be contained in the state vector. Conversely, if the time delay was too large then information about the dynamics of the system may be lost and can result in random information (Abarbanel, 1996; Baker and Gollub, 1996). Selection of the appropriate time delay was performed by using an average mutual information algorithm (Equation 2; Abarbanel, 1996).

$$I_{x(t),x(t+T)} = \sum P(x(t), x(t+T)) \log_2 \left[\frac{P(x(t), x(t+T))}{P(x(t))P(x(t+T))} \right] \qquad \text{Equation (2).}$$

where T was the time delay, x(t) was the original data, x(t+T) was the time delay data, P(x(t), x(t+T)) was the joint probability for measurement of x(t) and x(t+T), P(x(t)) was the probability for measurement of x(t), P(x(t+T)) was the probability for measurement of x(t+T). The probabilities were constructed from the frequency of x(t) occurring in the time series. Average mutual information was iteratively calculated for various time delays and the selected time delay was at the first local minimum of the iterative process (Abarbanel, 1996; Stergiou et al., 2004). This selection was based on previous investigations that have determined that the time delay at the first local minimum contains sufficient information about the dynamics of the system to reconstruct the state vector (Abarbanel, 1996).

It was additionally necessary to determine the number of embedding dimensions to unfold the dynamics of the system in an appropriate state space. An inappropriate number of embedding dimensions may result in a projection of the dynamics of the system that has orbital crossings in the state space that are due to false neighbors and not the actual dynamics of the system (Abarbanel, 1996). To unfold the state space we systematically inspected x(t) and its neighbors in various dimensions (e.g. dimension = 1, 2, 3,…etc.). The appropriate embedding dimension occurred when neighbors of the x(t) stopped being un-projected by the addition of further dimensions of the state vector (Equation 3).

$$\mathbf{y}(t) = [x(t), x(t + T), x(t + 2T), \ldots x(t + (d_E-1) T)] \qquad \text{Equation (3).}$$

where d_E was number of embedding dimensions, **y**(t) was the d_E-dimensional state vector, x(t) was the original data, and T was the time delay. A global false nearest neighbors algorithm with the time delay determined from the local minimum of the average mutual information was used to determine the number of necessary embedding dimensions to reconstruct the step time interval data series (Abarbanel, 1996). The calculated embedding dimension indicated the number of governing equations that were necessary to appropriately reconstruct the dynamics of the system (Abarbanel, 1996). The Tools for Dynamics (Applied Chaos LLC, Randle Inc., San Diego, CA, USA) software was used to calculate the embedding dimension for our data sets.

Lyapunov exponents were calculated to quantify the exponential separation of nearby trajectories in the reconstructed state space (Figure 1). This information was necessary to classify the local stability of the knee time series. As nearby points of the state space separate, they diverge rapidly and can produce instability. Lyapunov exponents from a stable system with little to no divergence will be zero (e.g. sine wave). Alternatively, Lyapunov exponents for an unstable system that has a high amount of divergence will be positive (e.g. random data). A chaotic system will have both positive and negative Lyapunov exponents. Although a positive Lyapunov exponent indicates instability, the sum of the Lyapunov exponents for a chaotic system remains negative and allows the system to maintain stability (Abarbanel, 1996; Baker and Gollub, 1996). This notion can be seen by inspecting the largest Lyapunov exponent for a sine wave (0), a chaotic Lorenz attractor (0.100), and random data series (0.469). Hence a chaotic system lies somewhere between a completely periodic system and a completely random system. The Chaos Data Analyzer (Physics Academy Software, Raleigh, NC, USA) was used to numerically calculate the largest Lyapunov exponent (LyE) for each time series.

INSERT FIGURE 1

Known deterministic/chaotic (the Lorenz attractor), random, and periodic (the sine wave) time series were also evaluated using the same nonlinear algorithms as the experimental data. The results from these data sets were used as a basis of comparisons.

Statistical Analysis

A 2X3 (side by speed) analysis of variance repeated on both factors was performed on the LyE parameter. This comparison allowed us to identify the effect of the speed protocol, the differences between the two sides (the ACL deficient and the intact contralateral knee) and the interaction between these two factors. A Tukey multiple comparison post-hoc analysis was used when appropriate. The a-level was set at 0.05.

RESULTS

Significant differences were found between the ACL deficient and the contralateral intact knee [$F(1,18) = 5.793$, $P = 0.04$]. Specifically, we found that the ACL deficient knee exhibits larger LyE values than the contralateral intact knee (Table 1). No significant differences were found for the LyE values among the three speeds. No significant interaction was found.

INSERT TABLE 1

To develop a basis for comparison, we calculated the LyE for a known chaotic (the Lorenz attractor), a random and a periodic (the sine wave) time series (Table 1). Positive values were obtained for both chaotic and random time series (Table 1). The LyE for the chaotic time series was smaller than that of the random time series. The periodic time series had LyE that was zero. If we compare these results to the results from our time series, we can see that our LyE values are closer to the chaotic time series.

DISCUSSION

In the present study we examined the effect of walking speed on functional dynamic knee stability. Functional dynamic stability was assessed in terms of local stability, which was described by Dingwell and Cusumano (Dingwell and Cusumano, 2000) as the sensitivity of the system to small perturbations. The stride-to-stride variations reflect precisely those perturbations. We hypothesized that walking speed will significantly affect local stability in ACL deficient individuals and this effect will be greater for the ACL deficient knee when compared with the contralateral intact knee. We used nonlinear measures since traditional linear measures (i.e. standard deviation, coefficient of variation) just provide a measure of the amount of variability that is present. Furthermore, as stated previously, traditional linear tools can mask the true structure of motor variability, since few strides are averaged to generate a “mean” picture of the subject’s gait. In this averaging procedure, the temporal variations of the gait pattern may be lost. On the contrary, nonlinear techniques focus on how variations change in the gait pattern over time.

The ACL deficient knee was found less sensitive to the small perturbations that may occur during locomotion. This was based on the significantly larger LyE values that the ACL deficient knee exhibited for all walking speeds (Table 1). Thus, the ACL deficient knee is more locally unstable than the contralateral intact knee. Several researchers have stated that impairment of the dynamical properties of human gait (i.e. changes in local stability) reflects an impairment of a functional component and/or altered nonlinear coupling between components (Hausdorff et al., 2000; Lipsitz and Goldberger, 1992; Vaillancourt and Newell, 2002). This could explain the differences in local stability between the ACL deficient knee and the contralateral intact knee. Actually, it has been demonstrated that the ACL apart from having mechanical properties, incorporates mechanoreceptors (Solomonow and Krogsgaard, 2001; Sjolander et al., 2002; Johansson et al., 1991) and therefore, its loss is associated with a loss of afferent proprioceptive input. Furthermore, ACL deficiency has been associated with changes in the central nervous system (Valeriani et al., 1996).

Our results showed no significant effect of the walking speed on the LyE values. This result may signify that the ACL deficient individuals alter their gait patterns to maintain their local stability when they walk faster. However, while local stability is preserved with different walking speeds, imbalances and differences between sides in terms of local stability still remain. Regardless of the walking speed, the ACL deficient knee is more locally unstable when compared to the contralateral intact knee. This could provide a possible explanation for the increased amount of future knee pathology in ACL deficient knees (Hawkins et al., 1986; McDaniel and Dameron, 1980; Daniel et al., 1994). It is possible that the altered dynamical properties of the ACL deficient knee lead to lack of ability to cope with various perturbations. Therefore, the ACL deficient knee is less able to adjust to the unpredictable and ever changing environmental demands. Thus, the ACL deficient knee over time develops further knee pathology possibly in terms of osteoarthritis and meniscal damage.

The above results provide also ground for an interesting hypothesis regarding local stability. It is possible that changes in local stability may in fact be the consequence of modifications not only in the deterministic operation of the adaptive complex control systems, but also in intrinsic stochasticity (noise). For example in the ACL deficient knee, while the deterministic properties of gait were preserved, a decrease in local stability was also observed. It is possible that local stability can actually be represented by a continuum. The two ends of the continuum are complete periodicity and complete randomness. A “healthy” optimal local stability by a motor system is somewhere between the two ends. Decreases or losses can make the system more rigid and less adaptable. Increases can make the system more noisy and unstable, like in the ACL deficient knee. This theoretical model predicts that the ACL reconstructed knee will be at the opposite end of the continuum and such a knee will exhibit increased local stability and lack of adaptability. This hypothesis needs to be tested in the future.

A possible limitation of the study is that our subjects walked on a motorized treadmill instead of overground. Dingwell et al. (2001) found that treadmill walking can possibly affect measures of local stability and variability when compared to overground walking. On the contrary, Murray et al (1985) demonstrated that kinematic measurements during treadmill walking do not differ markedly from overground walking. Furthermore, the collection of a large number of continuous data required for the calculation of stride-to-stride variability enforces the walking measurements to be collected on a motorized treadmill. In the present study, we also selected to use a motorized treadmill because we wanted to ensure that the speed remains constant for each condition. It has been shown that walking overground does not warrant a constant speed for a long period of time (such as in the case with multiple footfalls) due to intermittency (Minetti et al., 2001; Weinstein, 2001). It has also been found that speed can affect variability during walking (Winter, 1983; Oberg et al., 1993). Therefore, in the present study we selected to use a motorized treadmill to eliminate any confounding effects of the walking speed within conditions.

An additional limitation of the present study is that only data from the knee were analyzed. In future studies we plan to examine the other joints of the lower extremity using nonlinear methodology. It is possible that change in local stability at the knee can also affect the stability of the hip and the ankle. We also plan to examine differences between "copers" and "noncopers" (Eastlack et al., 1999; Lewek et al., 2003). Copers are patients with ACL rupture who return to activities involving cutting, jumping, or pivoting for a minimum of 1 yr, while noncopers are those who experience episodes of giving away (Fitzgerald et al., 2000). We speculate the noncopers will have decreased local stability. Lastly, our results need to be verified via comparisons with healthy controls to establish any differences in our nonlinear methods in terms of bilateral symmetry.

CONCLUSIONS

In summary, we used methods derived from nonlinear dynamics to examine the effect of walking speed on functional dynamic knee stability in ACL deficient individuals. We evaluated functional dynamic knee stability in terms of local stability. Our results showed that the ACL deficient knee utilizes a more locally unstable behavior than the contralateral intact knee regardless of walking speed. This behavior may reduce the ability of the injured knee to adapt to various perturbations, leading to future injury and pathology. As it was demonstrated in the present study, nonlinear methods help us get a better understanding and a more accurate evaluation of the behavior of the locomotor system over time. Such methods could be used for the accurate assessment of functional dynamic knee stability in clinical gait analysis.

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Figures

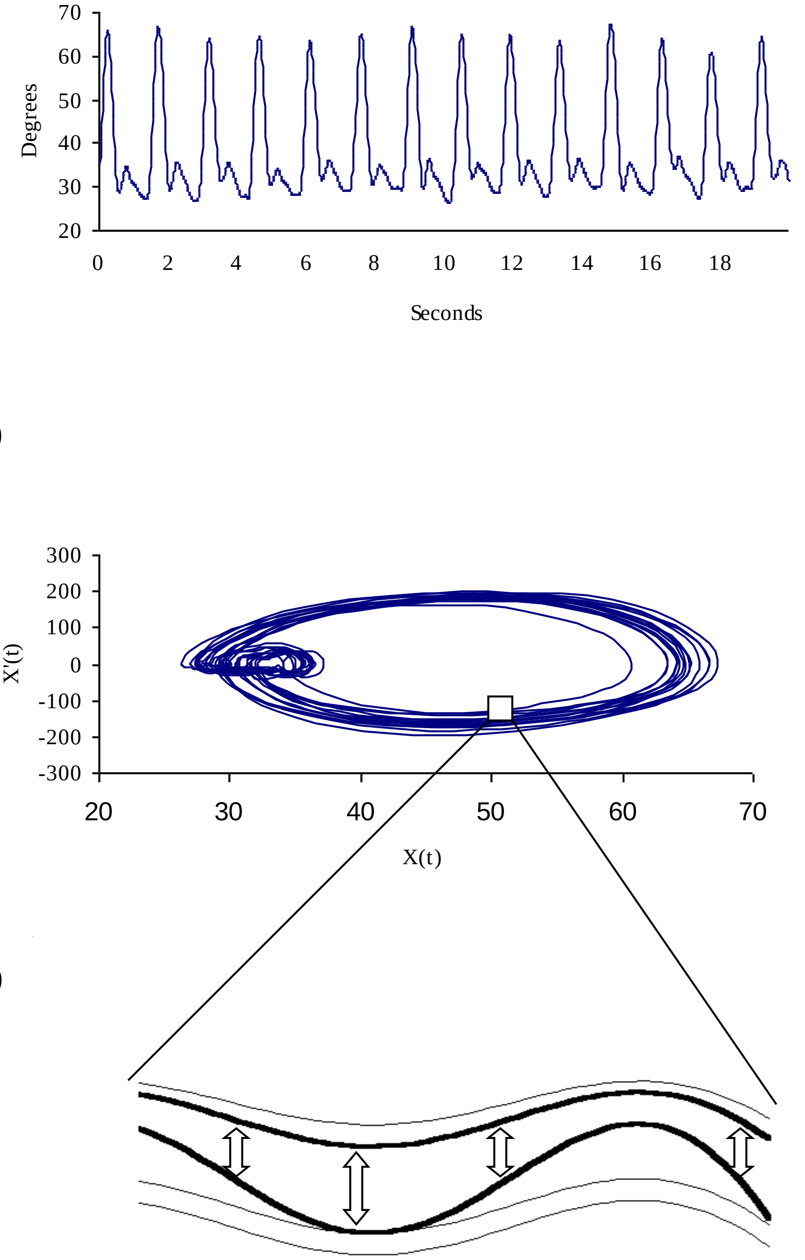
Figure 1. A graphical representation of the state space and the calculation of the LyE. (A) An original knee flexion-extension time series from an ACL deficient knee (B) A two dimensional state phase created by these time series. (C) A section of the state phase where the divergence of neighboring trajectories is outlined. The LyE is calculated as the slope of the average logarithmic divergence of the neighboring trajectories (Dingwell and Cusumano, 2000; Stergiou et al., 2004).

Figure 1

(A)

(B)

(C)



70
60
50
40
30
20
Degrees
0
2
4
6
8
10
12
14
16
18
Seconds
300
200
100
0
-100
-200
-300
X'(t)
20
30
40
50
60
70
X(t)

Table 1

Group means for Lyapunov Exponents (LyE) from the knee flexion/extension time series (standard deviation).

Variable	LyE
Periodic	0.000
Chaotic	0.100
Random	0.469
ACL deficient knee	
Self selected	0.1176 (0.0175)
-20%	0.1235 (0.0188)
+20%	0.1129 (0.0144)
Contralateral intact knee	
Self selected	0.1080 (0.0196)
-20%	0.1202 (0.0183)
+20%	0.1063 (0.0172)